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Enhancing Speech Impairment Support: Designing an EEG-Based BCI System for Turkish Vowel Recognition

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ABSTRACT

Brain-Computer Interfaces (BCI) have garnered significant attention as a technology that enables individuals to interact with their surroundings using brain activity. In the realm of BCIs, EEG-based systems offer a non-invasive and cost-effective means of monitoring brain activity. This study focuses on EEG-based BCIs and, in particular, aims to recognize Turkish vowel articulation intentions from EEG signals in healthy individuals. Turkish vowels, specifically 'A,' 'E,' and 'İ,' were chosen for their high frequency of use in the language. The study explores two distinct BCI system designs, one employing the Common Spatial Patterns (CSP) and Linear Discriminant Analysis (LDA) algorithms and the other utilizing the Discrete Wavelet Transform (DWT) and Support Vector Machine (SVM) algorithms. The results indicate that the second system, employing DWT and SVM, achieved a higher accuracy rate (80.2%) compared to the first system (67.7%), showcasing the superior performance of the DWT algorithm. This research could be a significant step towards improving the quality of life for individuals with speech impairments. The ability of EEG-based BCI systems to recognize the intentions of Turkish vowel articulation could aid these individuals in expressing their thoughts and intentions. Ultimately, this study contributes to the ongoing efforts to harness technology in ways that can significantly improve the lives of individuals with speech impairments.

1. INTRODUCTION

Various devices, software, and systems are designed to enhance the quality of life for individuals, thanks to the contributions of scientific advancements. BCI are among these technological developments.

The interpretation and understanding of brain signals using external devices and software systems has become one of the most popular research areas among researchers over the last 20 years [1-5]. These systems are known as BCI. Essentially, BCIs enable individuals to interact with their surroundings or use tools and systems solely through brain activity [2, 5-7]. Various methods are preferred for monitoring brain activity in BCI systems, including PET, MEG, EEG, NIRS, and fMRI [2, 8].

Due to its low cost and ease of application compared to other medical techniques, research on EEG-based BCI systems has gained momentum [8]. The invasive method involves a medical procedure with a high risk for life. In the non-invasive method, a healthier structure is established by observing electrical potential differences between neurons using electrodes placed on the individual's scalp [9]. This study is implemented on an EEG-based BCI system.

One of the distinguishing features among EEG-based BCI systems is the criteria used to evaluate brain signals. In EEG-based BCI systems, researchers typically perform observations of ERP (Event-Related Potential), SCP (Slow Cortical Potentials), VEP (Visual Evoked Potentials), and Sensory Motor Rhythm [10, 11].

- ERP: Electrical potential differences that occur in brain signals after a stimulus are examined [12, 13]. Different wave forms such as P100, N170, and P300 are evaluated in BCI systems in the literature. Each of these ERP components is examined in brain signals for different purposes [4, 8, 13]. Among these components, the P300 component is the most frequently used in ERP-based BCIs [12, 14, 15]. P300 spellers [4] are the most commonly used application models in the P300 ERP wave form [3, 13].
- VEP: The overlap between the signal fluctuation frequency and the stimulus frequency is observed in brain signals [16]. VEP-based BCI systems are used for steering activities with a limited number of commands, such as controlling a toy car [16]. In the literature, various VEP-based BCI systems, like c-VEP and SSVEP, exist. In systems with complex command sets, it can be challenging for users to maintain focus on the stimulus within a limited time [17].
- SMR: The changes in the frequencies of brain signals are examined [18]. SMR observations are often encountered in Motor Imagery BCI systems [6, 13, 19]. It is found in areas such as helping people with physical movement difficulties

and its use in athlete training [20, 21].

BCI systems consist of three fundamental steps: preprocessing, feature extraction, and classification. During preprocessing, tasks like denoising, artifact removal, and the isolation of the relevant signal frequencies are conducted [7, 13, 22]. In the feature extraction step, the focus is on extracting the features that are thought to represent the signal in order to reduce the size of the signal data from the preprocessing step [2, 7]. In the classification step, the signal data is classified using an appropriate classification algorithm using the extracted signal features. After the classification process, the system output is generated [7, 18].

As mentioned above, EEG-based BCI systems are frequently encountered in the literature due to their ease of application and observation compared to other methods. In the study of Curtin et al. [12], researchers designed an EEG-based BCI system utilizing the P300 component for navigating a virtual environment. In this study, participants achieved an accuracy rate of 82-89% while navigating virtual mazes using the BCI system. In another P300-based study, researchers developed a BCI system to empower severely disabled individuals to use web browsers [23]. The researchers tested their system on 16 MS patients and 5 healthy individuals. As a result, MS patients achieved an average accuracy of 84.14%, while healthy individuals achieved an average accuracy of 95.75%. Based on their findings, the researchers concluded that their system could be used safely by MS patients [23]. In another study, researchers used a P300-based BCI system to control a robotic system that can be used to assist severely disabled individuals in their daily tasks [14]. In this study, researchers used the P300-based BCI system in two different tasks [14]. Kapgate used a hybrid BCI system based on SSVEP and P300 to control a QuadroCopter in a study conducted in 2022 [15]. In his study, Kapgate designed three different BCI systems: SSVEP BCI, P300 BCI, and SSVEP + P300 Hybrid BCI [15]. Magee and Givigi [24] developed a P300-based BCI system in 2021 for use in vehicle steering. In this system, which uses a genetic algorithm for the classification process, they achieved an accuracy rate of 78.3% for single-epoch signals and 79.9±5% for multiple-epoch [24]. They also achieved an accuracy rate of 88.8±10.1% when they applied their system in the real world [24].

The study serves as a notable example of VEP-based BCI systems [16]. In this study, researchers created a virtual keyboard application using a VEP-based BCI system. During the testing phase of their virtual keyboard application, all participants were able to type the required words in 6-11 seconds.

When examining examples of motor imagery MI-based BCI systems in the literature, we observe their utilization across various applications. An MI-based BCI system was developed for gait rehabilitation using PSD for feature extraction and LDA for classification [21]. In a test involving five healthy individuals within a realistic rehabilitation setting, the system achieved a classification accuracy of 0.67±0.07, demonstrating its ability to distinguish between various gait patterns with a certain degree of accuracy. It introduced an MI-BCI system designed for six American Sign Language (ASL) movements, achieving a 75% classification accuracy, indicating its ability to recognize a wide range of hand movements [25]. It featured an MI-BCI system utilizing a single EEG channel to understand right- and left-hand movements, achieving an 87.6% accuracy rate in offline testing [26]. It presented a comprehensive overview of MI-BCI systems, offering insights into various types and discussing challenges and limitations within this technology [10].

This paragraph provides a review of studies relevant to the topic at hand. Researchers developed a BCI system to classify the motor imagery of the English vowels “a” and “u”. The study achieved a classification accuracy rate of 68%-78% [27]. In the study of Matsumotoa et al. [28], researchers focused on classifying brain signals from imagined speech using SVM and restricted Boltzmann machines (RVM). The researchers suggested that could provide a starting point for further research in this area [28]. Researchers compared classification algorithms in BCI systems for imagined speech and mouth movement conditions [29]. Participants performed tasks involving five vowels, and classification was done in pairs. The study found that HMM and KNN algorithms achieved a 75% success rate in classifying imagined vowels. They also noted that the SVM algorithm did not yield promising results in the classification of imagined vowels. Researchers focused on the classification of two vowels using an EEG-based BCI system [30]. The researchers used linear and quadratic classification algorithms to achieve an average accuracy rate of 77.5%-100%. In the study of Bakhshali et al. [31], researchers used the Riemannian distances of CSD matrices of signals from imagined speech to classify EEG-based BCI systems. The researchers were able to increase the classification accuracy rate to 90.25% with their proposed method [31]. In the study of Hernández-Del-Toro et al. [32], researchers studied the extraction of word fragments in continuous EEG recordings. The highest F1 scores obtained on three different datasets were 0.73, 0.79, and 0.68 respectively [32].

This study aims to interpret Turkish vowel articulation intentions from EEG signals in healthy individuals. The goal is to assist individuals with speech difficulties in participating more effectively in their daily lives through BCI systems.

In the literature, speech-related studies are referred to as silent speech or speech imagery. In these studies, participants are asked to say or imagine a word or vowel silently [30, 31, 33, 34]. As can be seen from the studies [33-35], researchers have achieved different average accuracy rates ranging from 29.21% to 88.36% using different techniques. Researchers achieved an overall accuracy rate of 35.20% for vowels and 29.21% for words using five vowels and six words [35]. The researchers achieved an accuracy rate of 80.7% in classifying silently spoken words using EEG using DAN [33]. The researchers achieved a maximum accuracy rate of 88.36% in classifying EEG signals recorded by imagining five English words, and an average of 72.73% and 69.41% using the alpha and theta channels, respectively [34]. Among these studies, the study of Iqbal et al. [30] partially focused on vowels, while the study of Liwicki et al. [35] directly addressed them. Notably, most studies in the literature do not mention Broca and Wernicke's areas of the brain, which are believed to be involved in language data processing [36, 37]. Furthermore, no similar study on Turkish vowels was found in the existing literature.

In this study, we designed and compared two systems for recognizing Turkish vowel articulation intentions based on EEG signals from healthy individuals. The first system, utilizing the CSP and LDA algorithms, achieved a 67.7% accuracy rate. The second system, employing the DWT and SVM algorithms, achieved an accuracy rate of 80.2%. These findings indicate the superiority of the DWT algorithm for this task. The study's results represent a promising step toward the development of a BCI system aimed at enhancing the daily lives of individuals with speech impairments.

In the study of Bakhshali et al. [31], the researchers explored the use of the correntropy spectral density (CSD) matrix and Riemannian geometry for EEG signal classification, demonstrating improved accuracy compared to other methods. It introduces a new matrix and distance metric based on CSD matrices. This study is closely related to our work, and the researchers obtained an average performance rate of 77.19%.

The researchers aim to explored EEG's potential for silent communication by decoding imagined speech from recorded brain waves. EEG signals were recorded at the University of California, Irvine (UCI) from 7 volunteer subjects, imagining syllables /ba/ and /ku/ were preprocessed and used for classification, indicating feasibility in identifying imagined speech. The final results show a 72% success rate in classifying imagined syllables, with the method generalizing well across subjects [38].

In 2020, the researchers worked on vowel inference in certain CVC (consonant-vowel-consonant) words. The accuracy rates of the two systems produced as a result of the study were obtained as 72% for RNN and 80% for DBN [39].

In one of the earliest studies in this field, the researchers introduced a brain-computer interface control scheme for a speech prosthesis. They utilized vowel speech imagery recorded through electroencephalography, employing optimized spatial filters and a nonlinear support vector machine. The overall classification accuracy achieved ranged from 68% to 78%, indicating substantial potential for its application as a speech prosthesis controller [27].

The study conducted explored imagined speech in EEG-based BCIs, aiming to simplify and improve neural network models for classifying vowel and word patterns. Using a dataset of 15 subjects, the study validates and simplifies a convolutional neural network (CNN), achieving lower but still competitive accuracy. The findings suggest the potential of transfer learning to enhance the effectiveness of neural networks in classifying imagined speech. The researchers obtained a considerably low success rate as a result of the study [40].

1.1 Brief information and contributions to the literature

BCIs have emerged as a groundbreaking technology, allowing individuals to interact with their environment through the interpretation of brain activity. Among various BCI modalities, Electroencephalography (EEG)-based systems have gained prominence due to their non-invasiveness and cost-effectiveness in monitoring brain activity. This study delves explicitly into the realm of EEG-based BCIs, focusing on the recognition of Turkish vowel articulation intentions from EEG signals among healthy individuals.

The chosen Turkish vowels 'A,' 'E,' and 'İ' hold significance in this research for their frequent usage in the Turkish language. By exploring two distinct BCI system designs and employing different algorithmic combinations, the study aims to contribute valuable insights into the field. The first design utilizes CSP and LDA, while the second design integrates DWT and SVM algorithms.

The subsequent discussion outlines the innovations brought forth by this study, encompassing algorithmic performance comparisons, the prominence of DWT, and the potential applications for individuals with speech disorders. Ultimately, this research endeavors to advance the development of BCI technology, particularly in the context of aiding those with speech impairments. The recognition of Turkish vowel articulation intentions through EEG-based BCIs has the potential to enhance the lives of individuals facing communication challenges significantly. As we delve into the subsequent sections, we dissect these contributions in greater detail.

1. Focus on Turkish Vowels: The article endeavors to develop an EEG-based BCI system centered on the recognition of Turkish vowels, specifically 'A,' 'E,' and 'İ,' which are frequently used in the Turkish language. This contribution may enhance effective communication tools for Turkish speakers, making it a valuable addition to the literature.

2. Algorithm Combinations and Performance Analysis: The study compares the utilization of CSP and LDA algorithms in the first system with DWT and SVM algorithms in the second system. This approach provides valuable insight into understanding the impact of different algorithms on the performance of EEG-based BCI systems.

3. Prominence of DWT: The results demonstrate that the second system employing DWT and SVM achieves a higher accuracy rate compared to the first system using CSP and LDA. It suggests a prospective effectiveness of DWT in tasks such as Turkish vowel recognition within the literature.

4. BCI Applications for Individuals with Speech Disorders: The research emphasizes the potential use of EEG-based BCI systems for individuals with speech disorders. This contribution may facilitate the development of future BCI applications aiming to enhance the daily lives of individuals with speech impairments.

5. Advancing Quality of Life through Technology: The article suggests that the ability of EEG-based BCI systems to recognize Turkish vowel articulation intentions could assist individuals with speech disorders in expressing their thoughts and intentions. This result could be considered a significant step towards leveraging technology to improve the quality of life for individuals facing speech impairments.

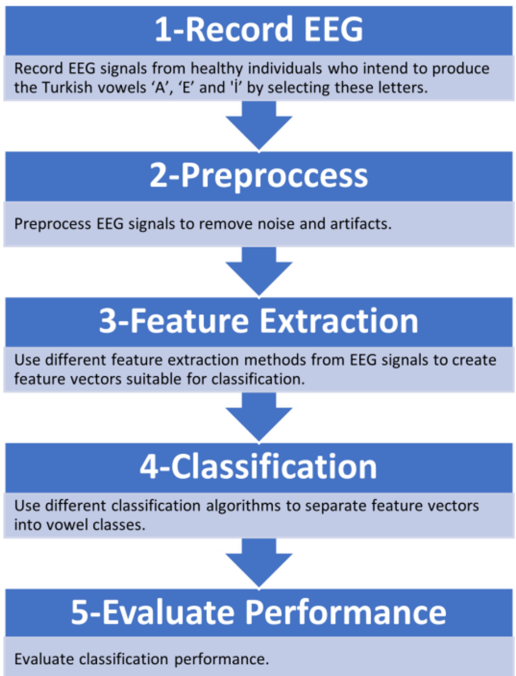


Figure 1. Steps of the study

To sum up, this investigation into Turkish vowel recognition makes a meaningful contribution to the advancement of EEG-based BCI systems. Additionally, it addresses the potential enhancement of the quality of life for individuals with speech disorders, thus providing valuable insights into the academic discourse.

We conducted our study by following the steps in Figure 1.

2. MATERIALS AND METHODS

2.1 Physical conditions and equipment

The EEG signals of the participants were recorded in a quiet environment. The study, conducted with a total of 5 participants aged between 26 and 52, exhibits a gender distribution of 2 females and 3 males. Participants sat comfortably in chairs with armrests and received instructions for the tasks via a monitor placed in front of them. Since the volunteers in the study had not previously undergone such recordings, they were provided with instructions on the EEG signal recording process after a brief overview of the study.

The EEG signals were captured and recorded using the EMOTIV EPOC+, a mobile EEG recording device from the EMOTİV company. The EMOTIV EPOC+ has 14 EEG channel sensors, and electrodes in both mastoid areas for reference values. The technical specifications of the EMOTIV EPOC+ device are as follows:

- The electrode array has been prepared according to the internationally accepted 10-20 system.
- The recorded electrode points are: AF3, F7, F3, FC5, T7, P7, O1, O2, P8, T8, FC6, F4, AF4.
- The frequency sampling rate can be set to 128 or 256 Hz.
- The signal measurement sensitivity is 0.51 µV.
- It has wireless connectivity.
- The sensors are saline-soaked felt pads.
- The electrode arrangement has been prepared according to the internationally accepted 10-20 system.

EMOTIV EPOC+ is a portable EEG system with 14 high-resolution channels, designed for rapid fitting and easy measurement in practical research. It's compatible with EMOTIV software and standard data formats, intended for research and personal use. The system uses saline-based wet sensors for quick setup, supports wireless data transmission at 128 or 256 Hz, enabling high-resolution brain data recording in mobile settings [41].

2.2 Experimental environment

In the experiment, the participants were asked to:

- Pronounce three random vowels once each, for a total of ten times.
- Next, imagine pronouncing the same vowels in a random order, once each in your mind.

The letters 'A', 'E', and 'İ' were chosen because they are the most frequently used vowels in Turkish [42].

Before the experiment, the participants were given the following information:

- Prior to connecting the EEG device, participants received instructions on how to perform the motor movements and mental simulations related to these actions.
- After adjusting the EEG device for the individual, they were introduced to the experiment environment through a PowerPoint presentation.

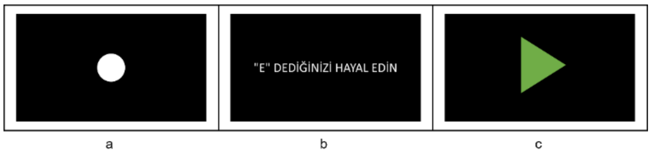


Figure 2. (a) Command preparation notification; (b) Command content notification; (c) Command execution notification

The experiment procedure is as follows:

1. Participants are instructed to prepare for a new command when the screen in Figure 2(a) is displayed during the PowerPoint presentation, which remains on for 1 second.
2. The screen in Figure 2(b), indicating the command content, is then shown for 2 seconds. Participants observe the motor movement they are required to perform, and additional software marks the location of the next motor movement in the EEG signal recording.
3. When the screen in Figure 2(c) appears, participants have 3 seconds to execute the command announced in Figure 2(b). The transition from Figure 2(b) to Figure 2(c) marks the individual's performed or imagined motor movement in the EEG signal recording (Figure 2). This process enables more precise determination of the beginning and end offsets of the signal block related to commands in the EEG recording.

During the 3-second duration shown on the screen in Figure 2(c), participants are instructed to perform the given command only once. This instruction is provided to participants before the registration process begins. The process continues in this manner until all commands are executed ten times. Following this, for the mental simulation of motor movements, the same PowerPoint presentation is restarted, this time with commands for mental simulations of the movements, and the process is completed.

The sequence of stimuli presented during recording for a single trial is shown in Figure 3, and also trial command indicator order is shown in Figure 4.

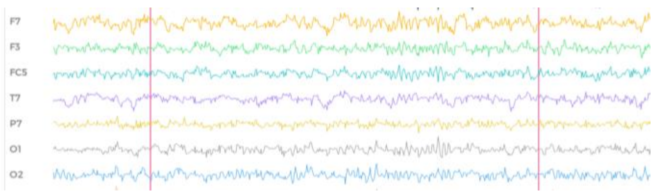
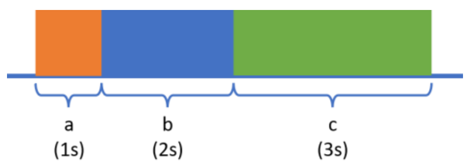


Figure 3. Individual EEG signal recording example (The red lines indicate the event start time)



(a) Trial start indicator; (b) Trial command indicator; (c) Trial command execution indicator

Figure 4. Trial order

2.3 System design

In the study, two distinct BCI systems were designed, both using the same EEG recordings. Since the preprocessing algorithms and techniques are identical in both systems, we provide a general description of the preprocessing stage. Subsequently, we separately analyze the feature extraction and classification stages of each system. Finally, in the Results section, we compare the outcomes achieved by the two systems.

2.3.1 Pre-processing

The preprocessing stage represents the initial step in preparing EEG signals for BCI systems. The primary objective is to eliminate artifacts and extract the desired frequency signal through specific filtering operations. Once the target signal frequency for the developed system is determined, practitioners often employ techniques such as frequency normalization or specialized filters [13]. Commonly used techniques in preprocessing include PCA, ICA, adaptive filters (common reference or surface Laplacian), frequency normalization (e.g., bandpass filters), and CSP [43]. Additionally, various other techniques have been applied in the preprocessing phase, as observed in the literature.

In the preprocessing stage of the first system, we initially removed the DC offset from the recorded signal by subtracting the mean of each channel. Subsequently, we applied a 5th-order Butterworth IIR filter with a frequency range of 8-30 Hz. The results obtained may vary based on changes in filtering parameters.

For this study, the event duration was set at 4 seconds, with an event start offset of 0.5 seconds. The impact of altering these values is detailed in the following sections.

2.3.2 First system design

The design of the first system is shown in Figure 5.

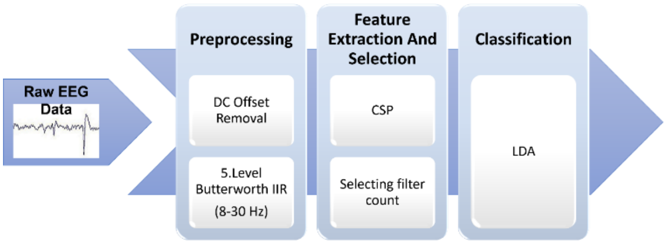


Figure 5. Design of the first system

<u>Feature Extraction.</u> EEG recordings are high-dimensional, resulting in significant computational costs. Therefore, prior to commencing the classification process, various techniques are employed to select relevant features and reduce the dimensionality of the EEG data [13]. Commonly used techniques for this process in the literature include PCA, CSP, GA, and DSLVQ. Notably, PCA and CSP are applied in both the preprocessing and feature extraction stages of the system [13]. Especially, CSP is widely used because of its competence in distinguishing between signal sets that are thought to represent classes [7, 44, 45]. PCA is also widely used to represent high-dimensional data with smaller data sets.

The basis of the CSP algorithm constitutes the objective function.

$$J(\omega) = \frac{w^T X_1^T X_1 w}{w^T X_2^T X_2 w} = \frac{\omega^T C_1 \omega}{\omega^T C_2 \omega} \quad (1)$$

where, T transpose, C_i, spatial covariance of class i, X_i, [#Channel x #Trial Sample] of class i, w, spatial filters.

From this relation, we encounter the generalized standard eigenvalue and eigenvector problem as follows:

$$C_1\omega = \lambda C_2\omega \quad (2)$$

The solution to this problem equation also provides spatial filters for EEG signals. In projects utilizing CSP for feature extraction, bandpass filters are frequently employed in the preprocessing stage to process signals at specific frequencies. In this study, the CSP algorithm was employed for feature extraction, and the following steps were applied:

- In the preprocessing stage of the design, a 5th-order Butterworth IIR filter was utilized to obtain the 8-30 Hz frequency range in EEG recordings.
- Initially, feature matrices representing each event are computed. These matrices comprise 'eigenvalue' vectors, which are summarized representations of signal values.
- Following the identification of root vectors (eigenvalues) in the matrices, the number of filters is determined to select vectors that enhance the class differentiation of the matrices. In the specific system design, the default number of filters is set to 2 (Figure 6).

1,45992039980857	1,86204870027768	0,263384988403963	2,08872052158331	3,49052760090154
2,15825585124360	0,990592012714873	3,68929047758498	4,91526233234928	3,33263956701293
0,0774356281800948	2,44843819008012	1,34559713199278	1,50727474356033	0,890662272001689
4,92031862189577	1,69746706695379	2,11417807504404	3,50549377950463	0,640071998600863
0,835842049573280	4,75815232388864	2,73935450607422	3,33169425792213	4,99540197380680
0,531081724643319	4,60166019918282	4,71368492138467	2,69563232521428	0,855605331782161

Figure 6. Example of a filtered feature vector

<u>Classification.</u> In motor imagery (MI)-based BCI systems, the classification process results in the generation of movements or movement simulations from EEG signals. These can encompass hand movements, tongue movements, or even word outputs. The choice of classification algorithms in MI-BCI systems varies depending on the system designer's preferences, as there is no standard algorithm universally employed in these systems.

In MI-BCI systems, common classification algorithms include SVM, LDA, KNN, ANN, and others [6]. Recent years have seen the emergence of convolutional neural networks (CNN) and hybrid algorithms alongside these traditional methods [6]. The efficiency of the classification algorithm used also varies according to the study.

LDA is a widely used linear classification algorithm known for its computational efficiency and ease of application, making it a popular choice in various research studies. It works by reducing input dimensionality, enhancing class separation, and reducing within-class variance [6]. However, one of the primary limitations of LDA is its potential underperformance on complex EEG data [6]. Nonetheless, LDA has a significant advantage in that its performance remains relatively stable even with minor changes in the training data.

In this study, the classification was performed using the LDA algorithm. As previously mentioned, the results section provides the outcomes obtained by varying the number of training and test data. No fundamental parameter within the LDA algorithm structure was altered, ensuring consistency in classification accuracy.

2.3.3 Second system design

<u>Feature Extraction.</u> In the first system design, the CSP algorithm was employed for feature extraction, yielding promising results. However, in the second system design, the DWT algorithm was utilized to enhance performance further. The design of the second system is shown in Figure 7.

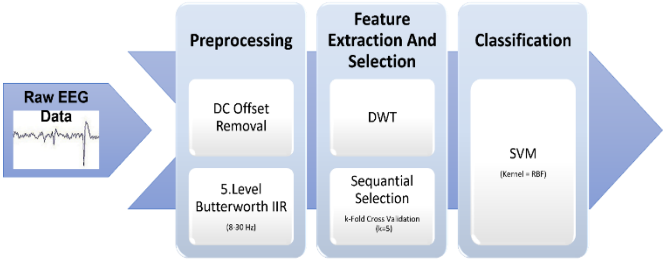


Figure 7. Design of the second system

In signal processing, DWT is widely applied for tasks such as noise removal, subwaveform analysis, especially in health-related signal processing studies, and feature extraction in image processing [46]. The DWT algorithm provides a time-frequency representation of a signal [47], dividing it into low-frequency and high-frequency components at each level. The low-frequency component is used for subsequent level operations, and this process continues until the signal is divided into subparts according to the specified level. In the feature extraction process utilizing the DWT algorithm, a maximum level of 9 was determined, following the Nyquist sampling rate principle (Eq. (3)).

$$L = \log_2 N \tag{3}$$

where, L is maximum DWT level, N is trial sample count.

As known, various regions of the brain have assumed specialized roles for the execution of specific functions [43]. In the brain, verbal skills are formed as a result of complex processes and require the use of different regions. The Broca and Wernicke regions on the left side of the brain play a crucial role in speech production [36, 37, 48]. In this study, signals from electrodes placed near Broca's and Wernicke's areas, known for their impact on verbal language skills in the brain, were investigated [43, 46, 48].

Before the classification step, features extracted using DWT were subjected to Sequential Feature Selection, a commonly used feature selection method. Initially, the selected feature vector length was set to 1/3 of the DWT-based feature vector length, which was later increased to 1/2. During feature extraction, various scenarios were explored, and system performance was enhanced by altering EEG channels, DWT bases, and wavelet forms used as band filters in the DWT algorithm.

To ensure the selected features represent the signal sample space as best as possible, the k-fold cross-validation (k = 5) technique was used. After the final feature vector of the signal was obtained, the classification process was started.

Classification. In the second system design, we employed the SVM classification algorithm, another commonly used approach in MI-EEG based BCI systems. The SVM algorithm utilized the Radial Basis Function (RBF) as the kernel function. Of all the acquired signals, 70% of the samples were allocated for training the SVM classification algorithm, while the remaining 30% of the dataset was reserved as test data to assess classification performance.

3. RESULTS

In this section, the results of the two system designs that have been studied will be presented as a table. In our study, we preferred the Accuracy method among the methods of Accuracy, Precision, Specificity, Positive Predictive Value, and Negative Predictive Value that can be used for performance evaluation because of its low calculation cost.

In this study, different signal processing and classification algorithms are compared to improve the performance of EEG-based BCI systems in recognizing Turkish vowel articulation intentions.

The data in Table 1 show the average and standard deviation values of the classification of EEG signals of five participants using CSP for feature extraction and LDA for classification algorithms. According to the average values, Participant 5's EEG signals are the strongest and most active, while Participant 1's EEG signals are the weakest and most passive. According to the standard deviation values, Participant 2's EEG signals are the most variable and inconsistent, while Participant 3 and 5's EEG signals are the most stable and consistent. As can be seen from the Table 1, the success of the first designed system remained at ~70%.

Table 1. Results from the first system design

	Participant 1	Participant 2	Participant 3	Participant 4	Participant 5
	50.00	67.50	68.75	58.33	64.75
	68.75	70.25	62.50	70.25	68.70
	52.38	47.37	65.00	60.12	58.35
	66.67	68.43	68.50	69.75	67.85
	57.15	68.43	58.25	62.65	69.25
Average	58.99	64.39	64.60	64.22	65.78
Standard Deviation	8.39	9.56	4.39	5.49	4.50

Notes: The top 5 Accuracy Rate (%) results from the first system design

Table 2. Result from the second system design

EEG Channels	DWT Coefficients	Wavelet Form	Accuracy Rate (%)				
			Participant 1	Participant 2	Participant 3	Participant 4	Participant 5
1,3,6,7	5,6,3,4,1	haar	62.50	75.00	65.00	77.00	80.00
1,2,3,4,5,6,7	3,1,4,5	db3	62.50	62.50	70.00	82.00	70.00
1,2,3,4,5,6,7	2,1	bior3.3	62.20	87.50	65.00	78.00	80.00
1,2,3,4,5,6,7	2,1	bior3.7	75.00	37.50	72.50	84.50	75.00
1,2,3,4,5,6,7	4,2	rbio1.5	75.00	62.50	67.50	79.50	70.00
		Average	67.44	65.00	68.00	80.20	75.00
		Standard Deviation	6.90	18.54	3.26	3.05	5

Notes: The top 5 Accuracy Rate (%) results from the second system design

The data in Table 2 show the accuracy rates of the classification of EEG signals of five participants using different DWT coefficients and wavelet forms. According to the average accuracy rates, the Bior3.3 wavelet form showed the best performance (74.54%). Bior3.7 wavelet form showed the lowest performance (68.80%). There are also significant differences in accuracy rates among participants. For example, Participant 2 achieved an accuracy rate of 87.50% with the Bior3.3 wavelet form and 37.50% with the Bior3.7 wavelet form. These results show that the selection of DWT coefficients and wavelet forms is essential in the classification of EEG signals [49].

The results show that the second system, using DWT and SVM algorithms, achieved a 12.5% higher accuracy rate than the first system, using CSP and LDA algorithms. This result reveals that the DWT algorithm is more effective in feature extraction of EEG signals and improves the performance of BCI systems.

4. DISCUSSION

We can discuss the strengths and weaknesses of each system design, the possible reasons for the differences in accuracy rates, and the implications for future research.

System 1 uses CSP for feature extraction and LDA for classification of EEG signals, using all 14 EEG channels on the device. The advantage of this method is that it is easy to implement and fast to compute. However, the disadvantage of this method is that it does not reflect the complexity and diversity of EEG signals sufficiently. Therefore, the accuracy rates of System 1 are low and variable.

System 2 uses a more advanced method for classifying EEG signals. System 2 obtains DWT coefficients using some of the EEG channels and different wavelet forms (haar, db3, bior3.3, bior3.7, etc.). The advantage of this method is that it can capture the features and patterns of EEG signals better and test the suitability of different wavelet forms. Therefore, the accuracy rates of System 2 are high and consistent. However, this method requires more parameter selection, and computation is slow compared to other methods.

The possible reasons for the differences in accuracy rates may depend on many factors, such as the source, quality, noise, sampling frequency, filtering method, classification algorithm, number, condition, experience, and skills of the participants of EEG signals.

For future research, we can infer that the selection of DWT coefficients and wavelet forms is essential for the classification of EEG signals. To better understand how these selections affect the performance, we can conduct more comprehensive and systematic experiments with different EEG channels, different DWT coefficients, different wavelet forms, different classification algorithms, and different participant groups in our future studies.

EEGs are very sensitive electrical signals that reflect brain activity [50]. Factors that can cause the breakdown of EGG signal potentials are Device Setup, Environmental Noise, Physiological Noise, and Cognitive Noise. In this study, EMOTIV Pro software was used to record EEG data. Thanks to the EMOTIV Pro software, errors that may occur during the device setup were prevented. The study environment was chosen as a laboratory where environmental noise was minimized. Participants were informed and relaxed beforehand to reduce physiological and cognitive noise. The raw data obtained from the EMOTIV Pro software were filtered using the MATLAB application to remove physiological and cognitive noises. In this way, the quality and reliability of EEG data were increased. Although our study has a small sample size, our results seem statistically significant and consistent.

5. CONCLUSION

In this study, our focus was on extracting certain Turkish vowels that individuals imagined pronouncing from EEG signals using an MI-BCI system. We designed two distinct systems, and the results are presented in the Results section.

As evident from the results, the second system, which utilized DWT and SVM, outperformed the first system employing CSP and LDA. These results underscore the effectiveness of DWT and SVM algorithms as observed in the literature.

Furthermore, the results tables for the second system reveal that factors such as EEG channels, DWT parameters, and wavelet forms significantly impact the outcomes. Additionally, due to the person-specific nature of EEG signals, different system configurations yield varying results among different individuals. The accuracy of the classification process is also influenced by the individuals' prior experiences with the system [47].

This study stands out in the BCI field as the first to focus on Turkish vowels and one of the few targeting the Broca and Wernicke areas of the brain.

We believe that this study can contribute to various areas of research aiming at enhancing the quality of life for individuals experiencing speech disorders, with the goal of improving their overall well-being. These areas can be listed as follows:

1. Diagnosis and Monitoring of Speech Disorders:

EEG-based BCI systems can recognize the intentions of individuals with speech disorders, aiding in the diagnosis and monitoring of speech disorders.

2. Enhancement of Vocal Communication Skills:

The study, by advancing techniques in recognizing Turkish vowel intentions, holds the potential to enhance vocal communication skills for individuals with speech disorders.

3. Integration with Assistive Devices:

BCI systems can be integrated with assistive devices, providing individuals with speech disorders the means to communicate more effectively in their daily lives.

4. Tailored Solutions to Individual Needs:

The study may be seen as a step towards personalizing BCI systems to meet the specific needs of Turkish-speaking individuals with speech disorders.

5. Low-Cost and Accessible Solutions:

EEG-based BCI systems are generally more cost-effective, offering speech disorder individuals access to more affordable technological solutions.

This study offers a potential application area for improving the quality of life for individuals with speech impairments, highlighting the importance of BCI technology. Individuals with speech impairments can express their thoughts and intentions through EEG-based BCI systems, which can increase their social communication and participation. Therefore, this study provides a significant contribution to the efforts of using technology to improve the lives of individuals with speech impairments. In future studies, different vowel sounds, different brain regions, and different signal processing and classification methods can be used to enhance the performance of EEG-based BCI systems further.

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